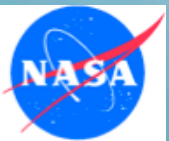


Use of machine learning techniques for identification of robust teleconnections to East African rainfall variability

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Outline

- Motivation & Background
 - SERVIR AST – Climate model downscaling
 - East African Rainfall variability
- Approach
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 - Hidden Markov Modeling & Compositing
- Results
 - Subseasonal variability
 - HMM States and Weather “regimes”
 - Connecting subseasonal to interannual variability
- Summary

Motivation – NASA SERVIR Applied Science Team

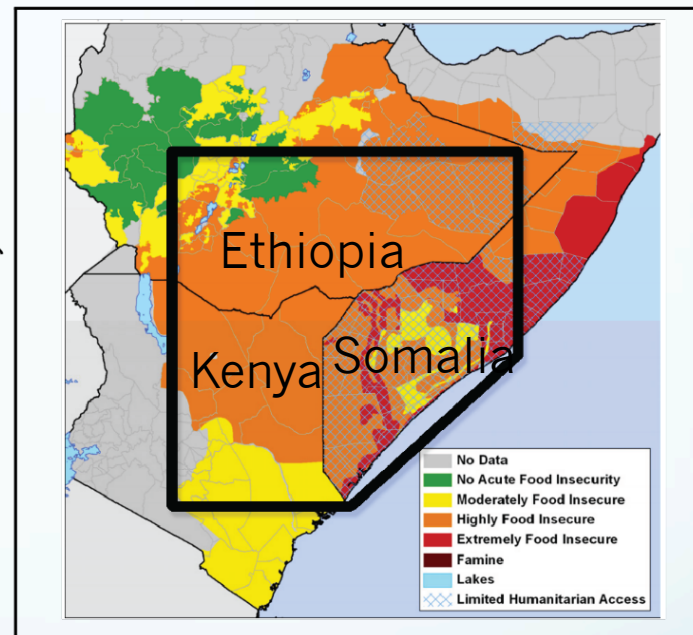
Leveraging Coupled Climate Model Projections for SERVIR Applications Science



Pete Robertson, PI,; **Brent Roberts**, Co-I, NASA/MSFC;
Chris Funk, Co-I, USGS/UCSB; **Brad Lyon**, Co-I, Columbia U. /IRI;
Mike Bosilovich, Co-I, NASA/GSFC/GMAO; **Siegfried Schubert**,
Collaborator, NASA/GSFC/GMAO

- The NASA/USAID SERVIR AST is focused on providing enhanced products, outlooks and projections (e.g.):
 - Agricultural modeling
 - Hydrologic modeling,
 - Air quality and landslide risk, among other
- Tailored for several hub regions
 - East Africa
 - Mesoamerica
 - Hindu Kush-Himalayan
- *Providing assessment of seasonal and climate model forecasts for these regions and development of scenarios for impact modeling*
 - *Requires downscaling in time and space (daily, ~10km)*
- (Wed) Poster 516, Climate Scenarios for the NASA/USAID SERVIR Project: Challenges for Multiple Planning Horizons

b. Food Security Outlooks

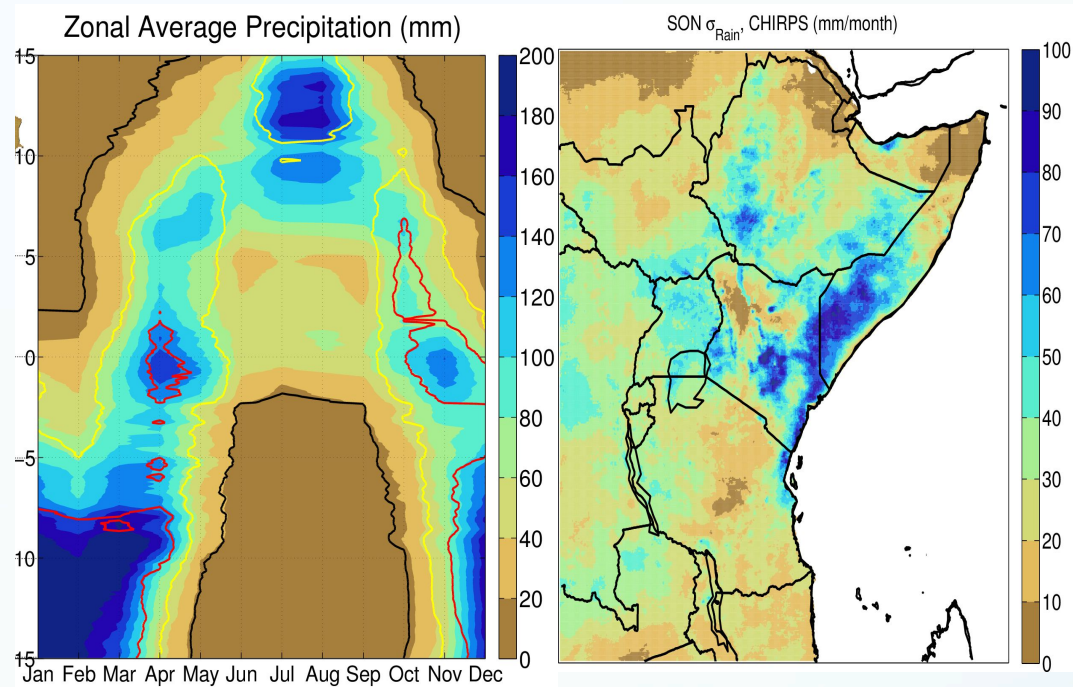


East Africa is a focus area of several efforts. There is a need for early warning of potential hazards for planning.

Motivation – East African Rainfall Variability

Equatorial East Africa (5S-5N)

- Two rainy seasons
 - MAM “long” rains
 - OND “short” rains
- Interannual variability of seasonal rainfalls appears to be more coherent for short rains rather than long rains
- Peaks in interannual variability are strongest over Uganda, Kenya, and southern Somalia.



Most studies of interannual variability have focused on seasonal mean variability.

- What can we learn about the characteristics of subseasonal variability in relation to seasonal mean variability?
- Can we appeal to machine learning approaches for providing a framework to examine patterns of subseasonal variability other than statistics of daily weather?

Approach - Datasets

MERRA – Weather/Climate Composites

- 1/3 x 2/3 resolution
- 1979 – NRT
- U,V – 850mb, 250mb
- Omega – 500mb
- Moisture convergence

Climate indices

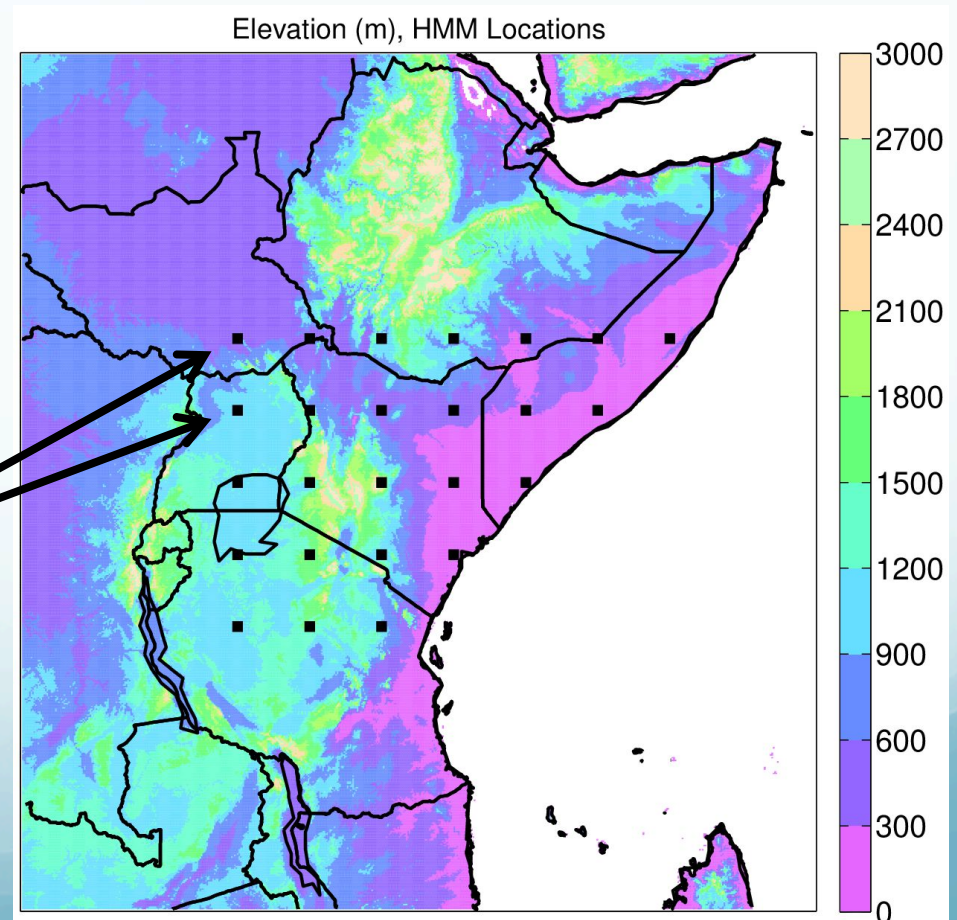
- Wheeler-Hendon MJO Index

Primary Domain – East Africa

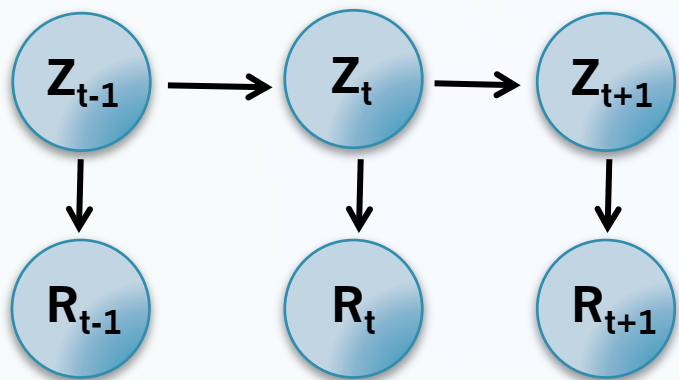
- 5S – 5N , 32.5E – 47.5E
- 25 stations (~2.5° apart)
- Coastal lowlands and interior highlands
- Focus on short rains (SOND)

CHIRPS – Rainfall

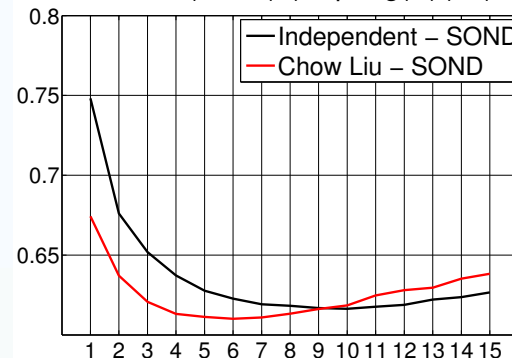
- ~5km resolution
- Merged IR/Model/Station
- 1981 – Near Real Time (NRT)



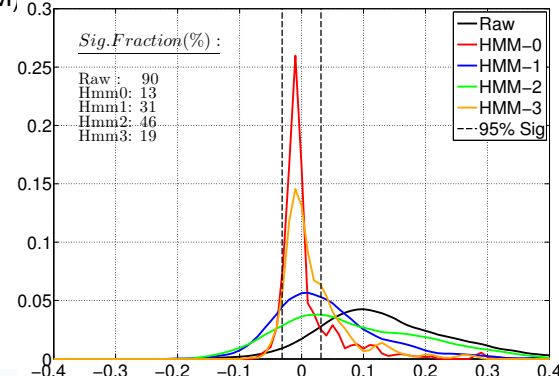
Approach – Hidden Markov Modeling



$$\text{Scaled BIC} = (-2 \cdot L(\Theta) + p \cdot \log(N)) / (N \cdot M)$$



Interstation Spearman Correlations – Raw , Within-State



- Directed graphical model that expresses the probability density of a sequence of observed variables (R_t) as the result of a Markov sequence of unobserved or latent states (Z_t)

- Links to machine learning

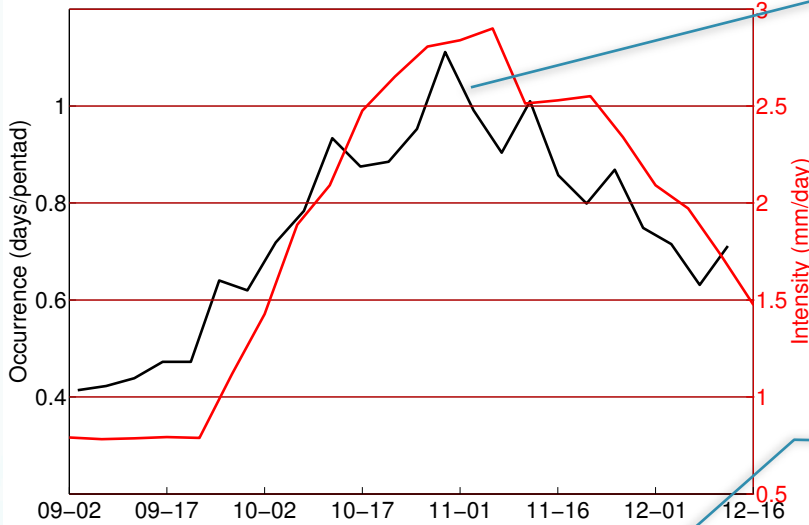
- Clustering: identification of potential hidden structures from observations
- Classification: assignment of sequence of vectors to a most likely sequence of hidden states (Viterbi algorithm)

HMM Model Training

- Use MVNHMM Toolbox (S. Kirshner)
- 4 states chosen for this analysis
- Use of Conditional Independence model
 - Only marginal improvement found by taking into account within-state dependence
- Interstation correlations reduced significantly by conditioning on states

Subseasonal Variability – Traditional View

Station Average, Subseasonal Cycle

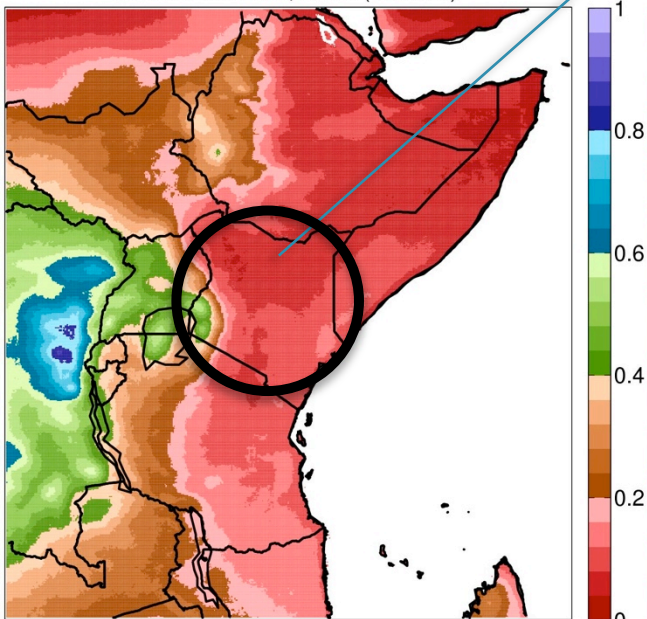


Rainfall occurrence and wet-day intensity covary strongly over the SOND period typically peaking in late October.

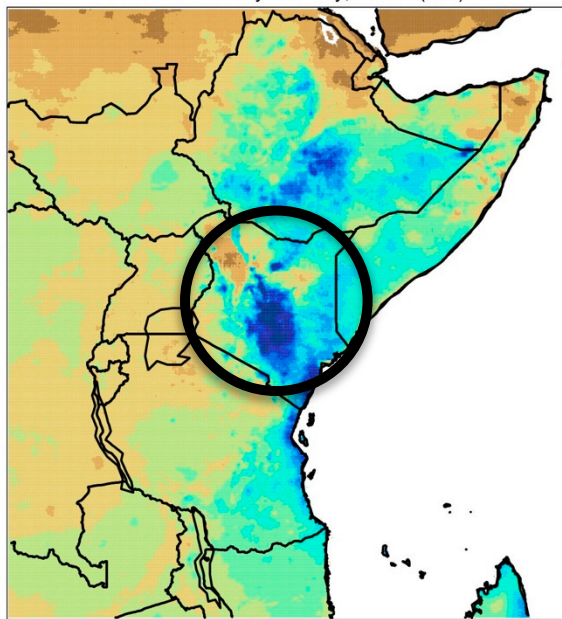
Distribution of Daily Rainfall

- 1) Infrequent
- 2) Intense
- 3) Short duration

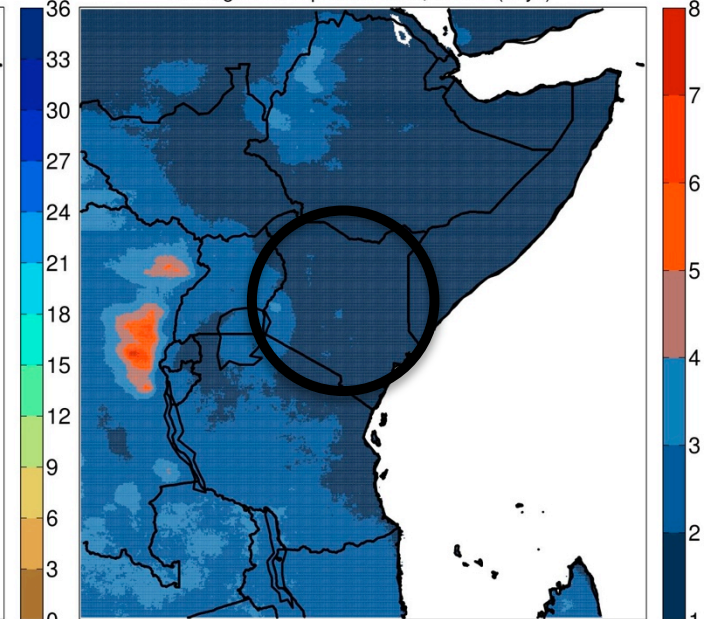
Rainfall Occurrence, SOND (fractional)



Rainfall Wet-day Intensity, SOND (mm)



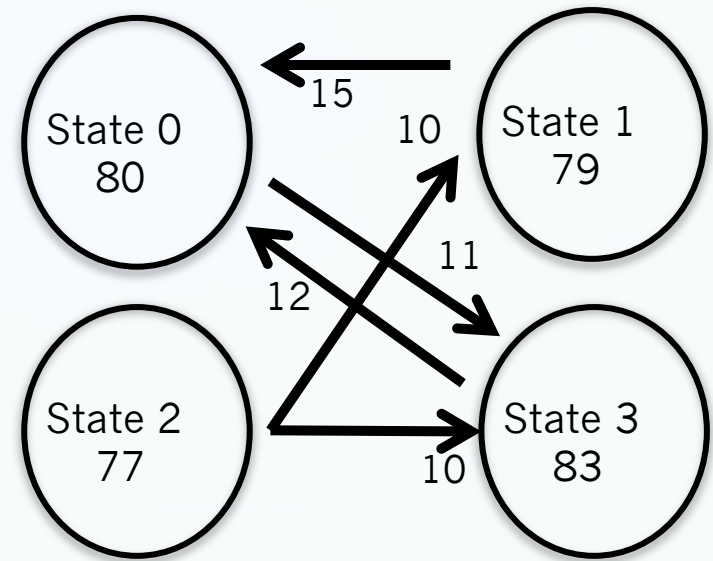
Average Wet-Spell Duration, SOND (days)



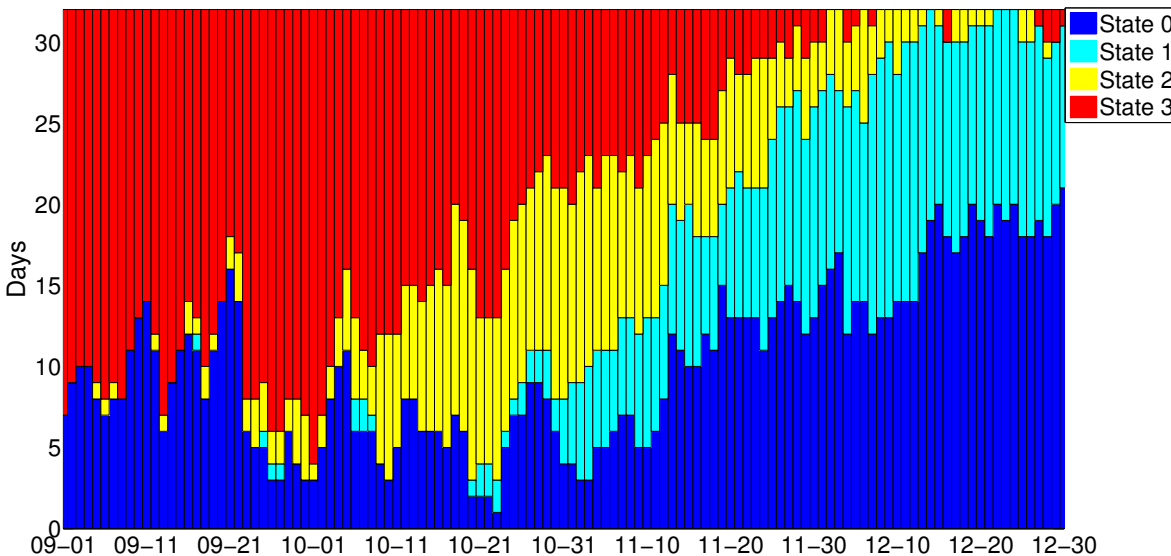
Subseasonal Variability – HMM View

Transition Probabilities (4 states):

- Very likely to remain in a particular state (persistence)
- Very unlikely to go from State 2 to State 0 directly (<3%)
- Non-stationary over the SOND period



Number of days in HMM State over 32-year record



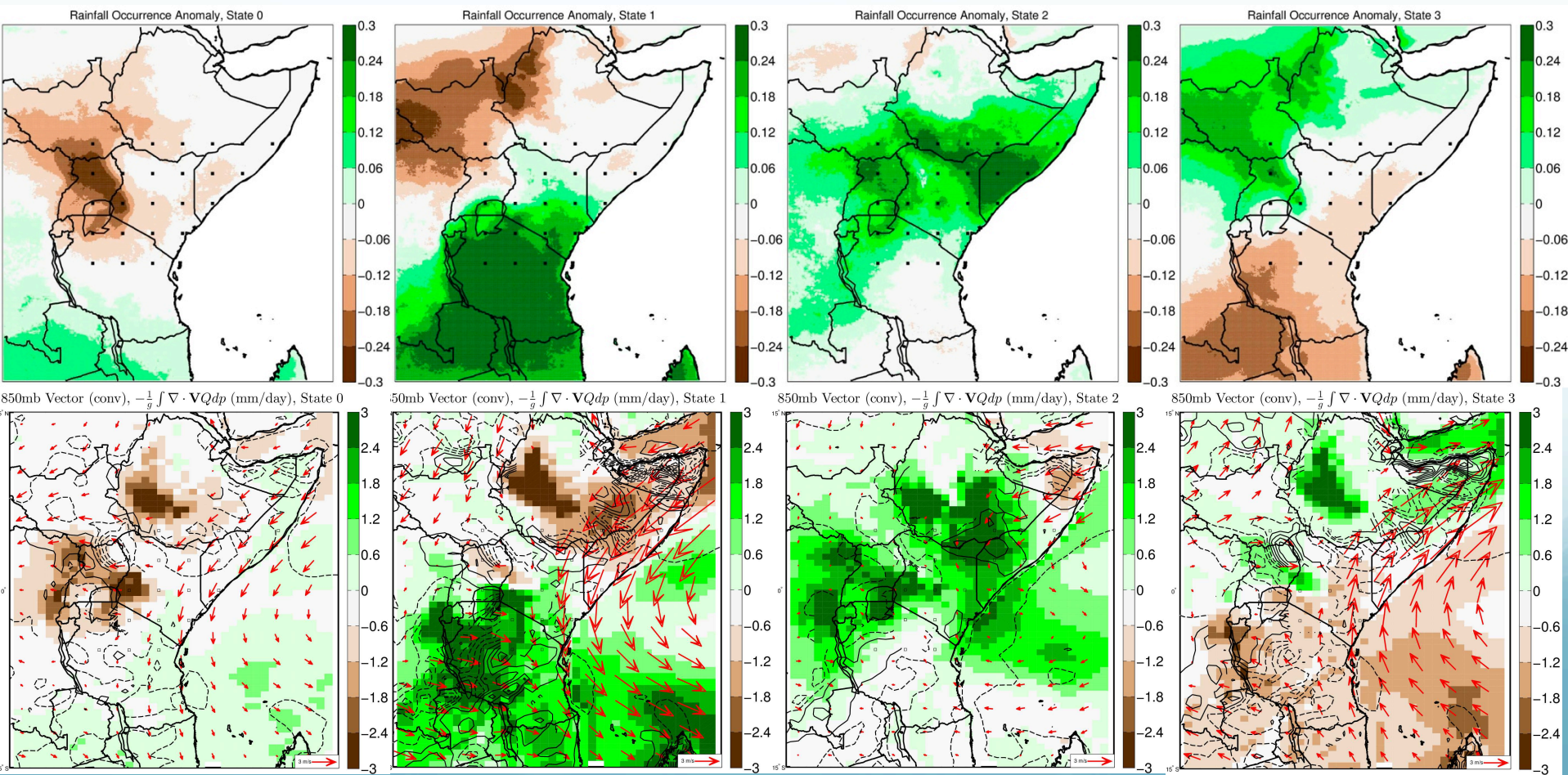
- Hidden capture an underlying evolution of rainfall variability within the short rains period.

3 → 2 → 1 → 0

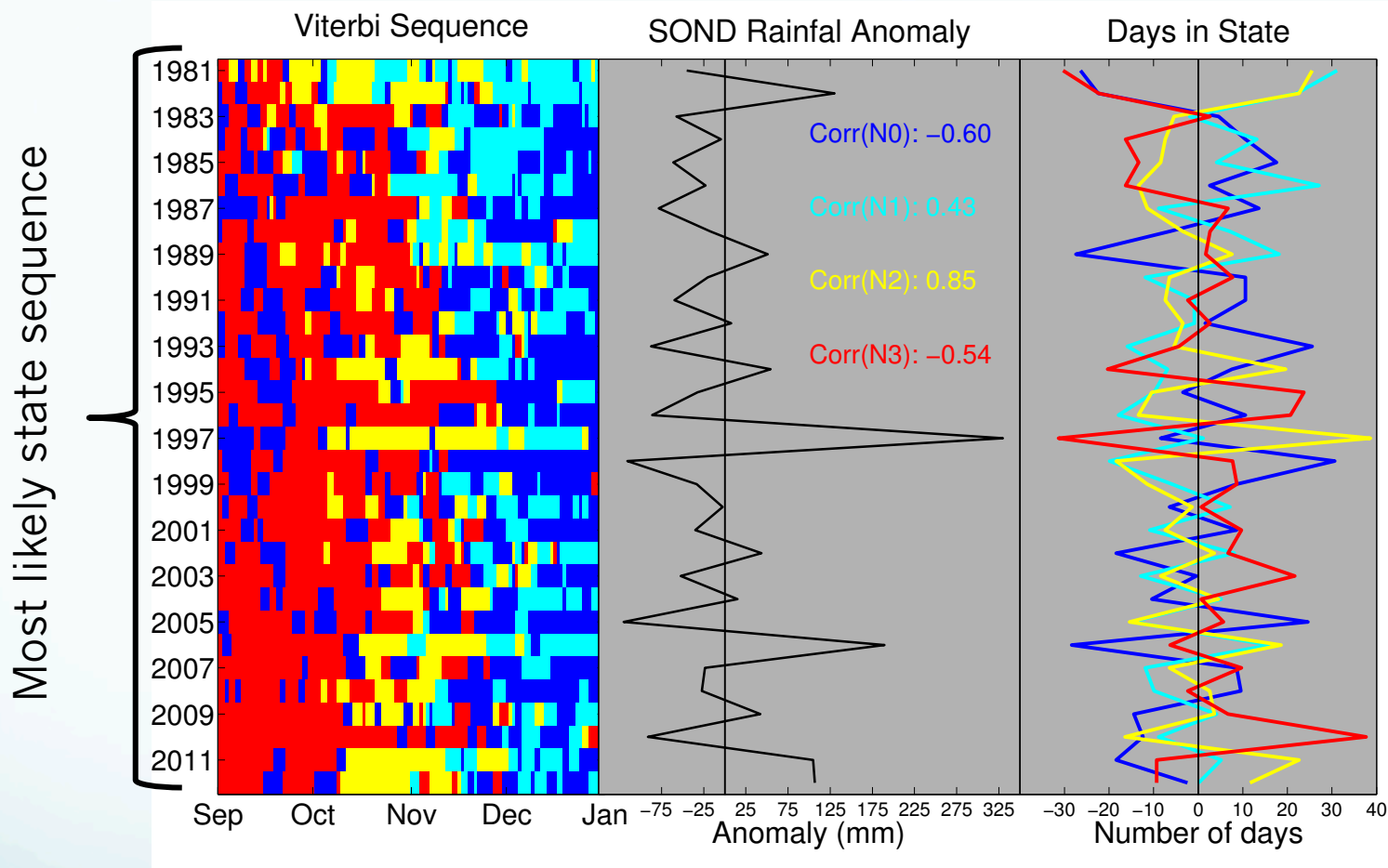
HMM States – Composite Meteorology

Composites of 850mb winds, moisture convergence, and rainfall frequency

- Progression from State 3 \rightarrow 1 : Similar to ITCZ progression but State 2 (the “wet” mode) does not show in monthly averages.
- No analog for State 0 (“dry” mode) in monthly averages either.
- Rainfall anomalies correspond strongly with anomalous moisture convergence

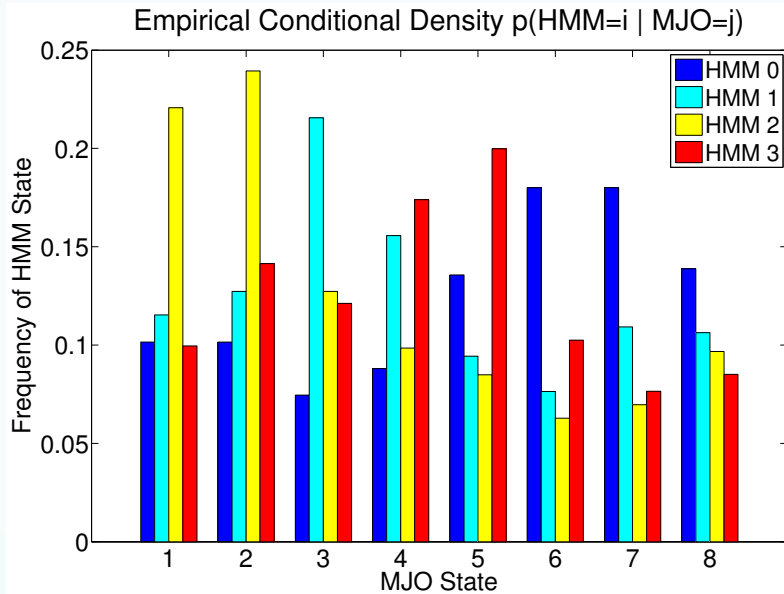


Subseasonal to Interannual variability

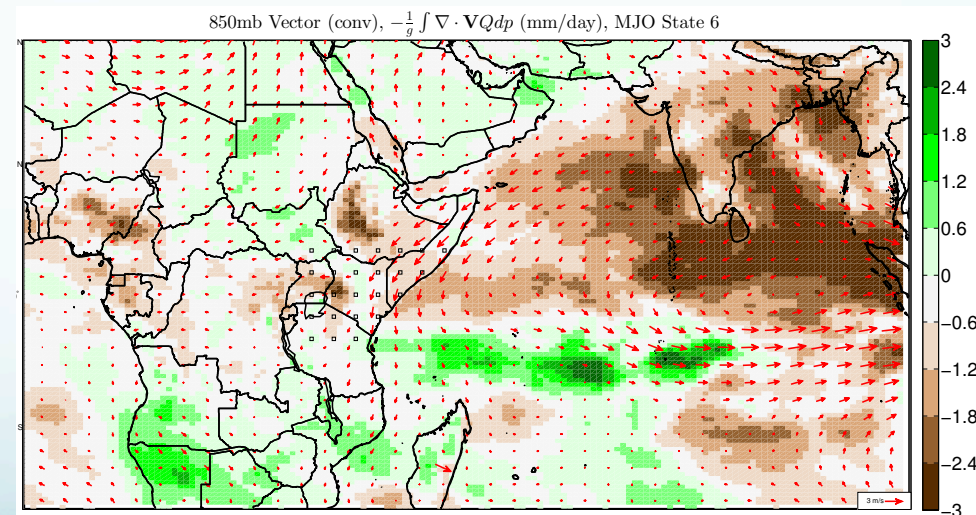
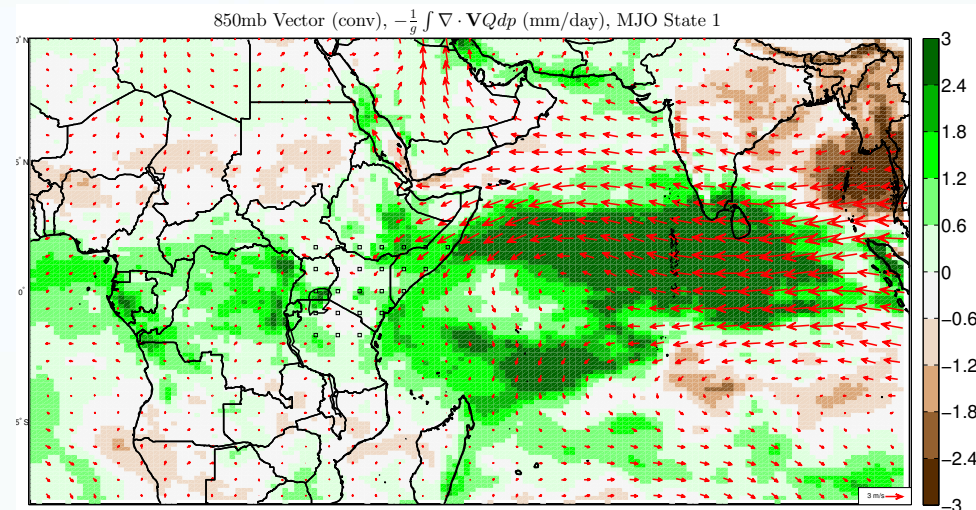


- Interannual seasonal rainfall anomalies are significantly correlated with interannual variations in the number of days in each HMM state.
- This is particularly strong (0.85) for the number of days in the “wet” state (2)

Connections to MJO Variability

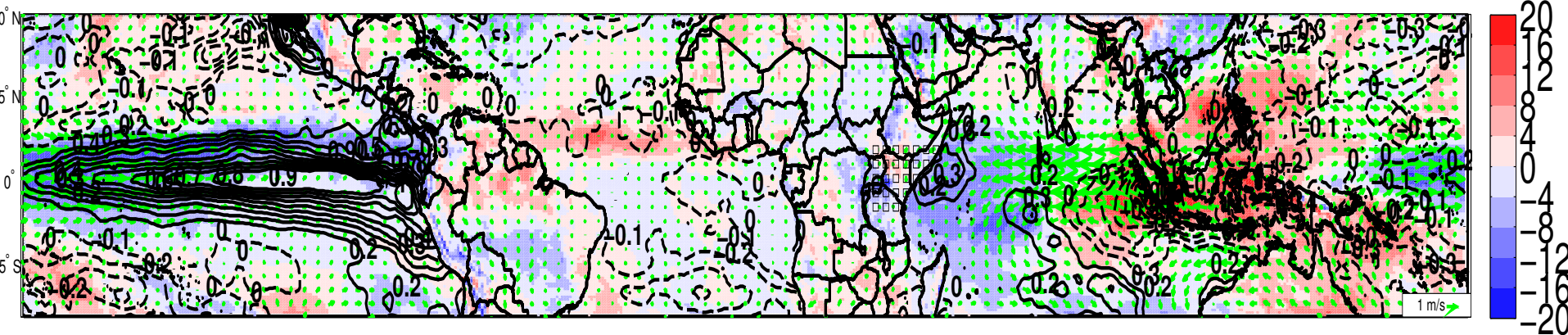


- “Wet” state (2) is most likely to be found occurs during MJO Phase 1 & 2
- “Dry” state (0) is most likely to be found occurs during MJO Phase 6 & 7
- MJO composites show very similar circulation anomalies to those found in compositing HMM states



Connections to ENSO & IOZM Variability

850mb Vector, Omega500 (shaded,hPa/day), SST (contour), Upper Quartile NDAYS_{HMM2}



Composites of seasonal anomalies for years with a high fraction of "wet" state

- Large-scale SST and circulation anomalies
 - El-Niño warming, east Indian cooling, west Indian warming
 - Anomalous subsidence over Maritime continent, ascent over west Indian
 - Anomalous westerlies over the Indian ocean

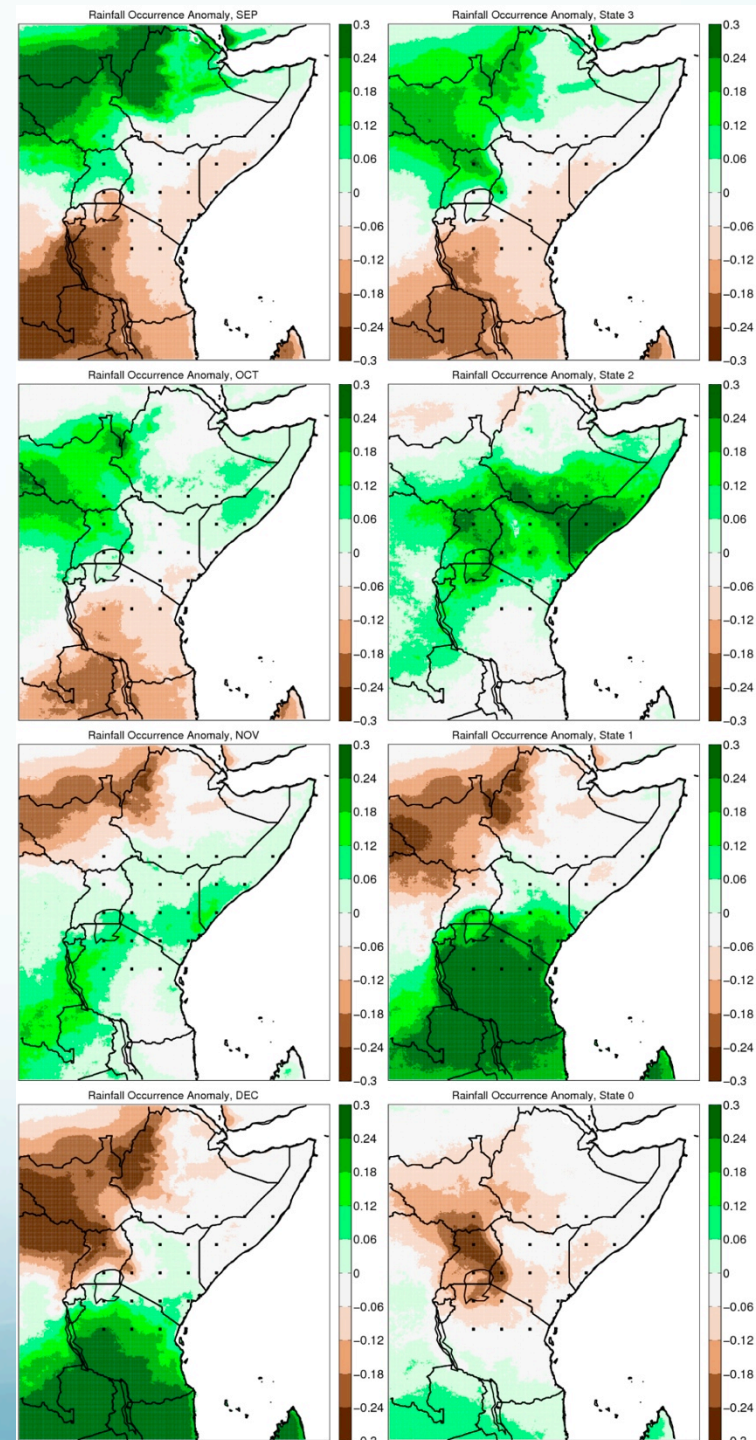
Reduced Walker cell over Indian sector → Increased moisture convergence and rainfall over equatorial East Africa

Summary

- **Hidden Markov models can be used to investigate structure of subseasonal variability.**
- **East African short rain variability has connections to large-scale tropical variability**
 - MJO – Intraseasonal variations connected with appearance of “wet” and “dry” states
 - ENSO/IOZM SST and circulation anomalies are apparent during years of anomalous residence time in the subseasonal “wet” state.
- Similar results found in previous studies, but
 - **We can interpret this with respect to variations of subseasonal wet and dry modes.**
 - **Reveal underlying connections between MJO/IOZM/ENSO with respect to East African rainfall**

Extras - 1

- Monthly averages (left) capture the large-scale seasonal progression of rainfall during the short rains season.
- However, there is no strong peak in anomalies over the equatorial East Africa regions at this monthly scale
- The HMM states appear to capture the two poles of the ITCZ progression (States 1 & 3)
- The HMM also captures two more regionally localized modes over EEA (a “wet” (2) mode and a “dry” mode(0))



Extras - 2

- Increases in the frequency of MJO State 1 are correlated with increases in the number of days in the HMM wet state.
- During MJO State 1, the west Indian ocean is typically warm while the east Indian ocean is cold (w.r.t. to the SOND mean).
- This SST pattern is also prevalent with what is considered the IOZM and also has been shown to have some connections with remote forcing by ENSO.
- In response (? , perhaps “coexistence”) to the anomalous SST gradient, anomalous pressure gradients are observed as is an anomalous low-level westerly circulation that weakens the Walker circulation and reduces the climatology export of moisture away from EEA.

